Empirical evidences on the deforestation drivers in Brazilian Savanna

July, 2021

Pedro Gabriel Meiners[Φ,*], **Alexandre Alves Porsse**[Φ], **Marcelo de Oliveira Torres**[△]

[Φ] Department of Economics, Parana's Federal University, Curitiba, Paraná, Brazil.

[△] Department of Economics, College of Economics, Business and Accounting, University of Brasilia, Brasília, Federal District, Brazil.

[*] **Correspondence:** Email: pg.meiners@gmail.com

Abstract

This paper aims o assess the economic, policy and climatic determinants of deforestation in the Brazilian Savanna (*Cerrado*). We estimate panel data models and spatial models (from 2002 to 2018) for 949 municipalities in the region. The results show that recent deforestation is responsive to government policies, measured by rural credit and environmental fines. Also, we evaluate the environmental Kuznets curve hypotheses, and conclude that it partially applies to the deforestation in the Brazilian Savanna. Moreover, we found some evidences showing that extreme periods of dry climate in the region plays a role on the deforestation process.

Keywords: Deforestation, Cerrado, Spatial Econometrics, Brazil, Agriculture

Resumo

Este trabalho tem como objetivo avaliar os determinantes econômicos, políticos e climáticos do desmatamento no Cerrado Brasileiro. Estimamos modelos de dados em painel e modelos espaciais (de 2002 a 2018) para 949 municípios da região. Os resultados mostram que o desmatamento recente responde à políticas governamentais, medidas por disponibilidade de crédito rural e intensidade de multas ambientais. Também avaliamos a hipótese da curva ambiental de Kuznets, concluindo que ela se aplica parcialmente ao desmatamento no Cerrado Brasileiro. Além disso, encontramos algumas evidências mostrando que períodos extremos de clima seco na região influenciam o processo de desmatamento.

Palavras-chave— Desmatamento, Cerrado, Econometria Espacial, Brasil, Agricultura

JEL codes: Q15, C23, Q28

Classificação ANPEC: Área 11- Economia Agrícola e Meio Ambiente

1 Introduction

Originally nearly 24% of the Brazilian territory was covered by a tropical savanna called Cerrado, with settlement in this area being sparse until the mid twentieth century. This scenario started to radically change in the 1960s and 1970s as new techniques and plant selection advancements promoted by the Brazilian Agricultural Research Corporation (EMBRAPA) allowed for Soybean cultivation in this tropical biome. From the 1980s onward an extensive land-use-land-cover-change (LULCC) process started in the area and Brazil became the world largest Soybean producer (CONAB, 2020) with clearly adverse impacts on the Cerrado biome. Some studies even predict that the savanna will be extinct by 2030 (Machado et al., 2004)

Given the extent of the deforestation in the Cerrado and the potentially large impacts on the ecosystem, it is surprisingly low the number of scientific studies focused on its causes. Traditionally, the studies on Brazilian deforestation, which started to come up particularly during the 1990s (Shukla et al., 1990; Skole and Tucker, 1993) focused on the Amazonian biome, probably as a response to the huge international scrutiny concerning the forest maintenance and the observed high levels of deforestation in the late twentieth century (Mahar, 1989; Binswanger, 1991).

Concerning the main drivers of deforestation, the literature in general is not consensual. Some, such as Allen and Barnes (1985) and Cropper and Griffiths (1994), suggest that population growth, by putting a pressure on the demand for wood based fuel and food and the subsequent agricultural expansion, is the leading cause; while others weight in urbanization as Ehrhardt-Martinez (1998) by recognizing that the shift from a rural to an urban society ended up by inducing an increase on the demand for forest resources causing deforestation (at least up to a certain level of urbanization).

Barbier (2004) argues that developing nations, especially those without natural reserves of oil and gas, have in agricultural land their only source of natural wealth, then the conversions of forest to farmland –as a result of international demand for food commodities– is an important driver of deforestation. There are also some studies concerned with the social drivers of deforestation such as Wyman and Stein (2010) that used smallholder surveys to analyse social influences in deforestation, finding a negative correlation between education, income and tenure to deforestation.

More specifically to the Brazilian case, research concerning deforestation can be separated into macro- and market-level studies. Earlier articles favored macro effects, such as, population pressure, country growth, and road network (Andersen, 1996; Pfaff, 1999). Recent literature has used panel data to identify correlation between deforestation and commodities prices mainly soybeans and cattle (Diniz et al., 2009; Rivero et al., 2009). Some studies also have analysed deforestation influenced by environmental policy such as in Assunção et al. (2015) which used panel regression to determine economic influences on Amazon deforestation, using prices on tradables and policy change at municipality level. This approach was then followed by Hargrave and Kis-Katos (2013) that also controlled for spatial aspects and fine enforcement and application.

In general their main findings point towards the agricultural pressures –driven by a combination of high commodity prices and currency devaluation– as the main incentives of deforestation on Brazilian biomes. With some studies highlighting the role of fine intensity or reservations markings, while others on the indirect impacts of socioeconomic variables on deforestation (Angelsen, 1999). Some studies find negative relationship between years of education and deforestation (Godoy et al., 1998; Godoy and Contreras, 2001), while others, positive (Pichón, 1997). Conventional wisdom also suggest that poverty is associated with higher levels of deforestation, nevertheless empirical studies suggest the opposite (Pendleton and Howe, 2002) with Zwane (2007) showing that due to imperfect labor markets, a rising income level may lead to higher land clearing levels.

This literature rarely focus on the Cerrado and strikingly lack a deeper discussion on the economic drivers of the Cerrado deforestation with the excessive reliance on stylized facts and on correlation exercises at best.[1]: Jepson (2005) used satellite data to identify significant loss of vegetation and a evidence that Cerrado can have a natural regeneration; Brannstrom et al. (2008) observed that the LULCC processes in the biome are not a spatially homogeneous process, with deforestation in Mato Grosso being more predatory than in Bahia; and Rocha et al. (2011) found that deforestation warnings where highly concentrated with 70% of all warnings between 2002 and 2009 emerging from the same 100 municipalities.

In this context this study aims to contribute to the literature on the economic drivers of the Cerrado by building up an econometric model that take into account market-based pressures on deforestation that allows for the analysis of crucial aspects of land use and land cover change in the biome, in the same manner that studies concerning Amazon have already demonstrated.

In the following section we establish the micro foundation of our theoretic model, in section 3 explain our data collection choices and pitfalls. Section 4 explains the empirical approach chosen and in section 5 some robustness tests are presented along with the modeling results. In section 6 we conclude.

2 Theoretical and Empirical Predictors of Deforestation

According to Angelsen (1999) open-access model, deforestation is dependent on the expected profit of newly cleared land. This profit is influenced by factors associated with traditional market conditions that influence profit-maximizing behaviour of the firm, be it commodity prices, labor and capital costs. de Araújo et al. (2021) proposes two theoretical approaches to analyse deforestation –particularly in Amazon. Using game theory, it is shown that individual decision on the exploitation of the forest natural resources leads to a tragedy of the commons equilibrium, a situation where there a no incentives for environmental maintenance. Based on Becker (1968) crime rational choice and deterrence theories, de Araújo et al. (2021) argues that illegal deforestation can be analysed as the rational decision where the perpetrator evaluate predicted profits of the deforestation against certainty, severity, and celerity of punishment.

Empirical studies of deforestation deterrence in Brazilian Amazon uses fines enforced by IBAMA (Brazilian Institute of Environment and Renewable Natural Resources) as the main punitive disincentive to illegal clearing. In what concerns certainty of punishment, Hargrave and Kis-Katos (2013) modeled intensity of IBAMA fine by deforested area impact on deforestation and found that there is strong evidence that higher surveillance can deter deforestation. De Souza et al. (2013), who studied impacts of rural technology, land concentration, and IBAMA embargoes on deforestation, arrived at mixed results concerning IBAMA activity, citing that IBAMA's fines and embargoes are of reactive nature and work on stopping deforestation on high deforestation areas, but have little proactive effect on deterring future deforestation.

Profitability of deforestation can come from immediate and future revenues. The first are profits generated by the immediate act of deforestation such as logging and charcoal production. For Cerrado the latter may exert a similar impact on deforestation as logging does to Amazon, since native species of the biome were responsible in 2005 for 34.5% of all charcoal produced in Brazil Duboc et al. (2007), the majority of it from

[1]For example by affirming that deforestation is a result of soybean farms expansion given its international prices.

non-sustainable plant extractions (PEVS, 2021). The medium- to long-term revenues will arise after formal settling in the land, by establishment of pastures or plantations, these are sensible to market fluctuations such as currency devaluation, input prices, and commodity markets. As for immediate sources of revenue, prices may have a lesser impact due to the speed of operations and low costs. Empirical studies such as Diniz et al. (2009) and Rivero et al. (2009) used panel data to find evidence of causality between cattle herd and soy cultivation area sizes and deforestation in Amazon. Assunção et al. (2015) and Hargrave and Kis-Katos (2013), using panel analysis at the municipality level, observed significant influence of prices (cattle, soy, wood and other crops) on deforestation in the Amazon.

Given possible revenue and punishments for deforestation there is a necessity to measure costs in the rational decision theory. According to Angelsen (1999) theoretical model, transportation cost is important for any rural producer, but it has a special importance to deforestation as agricultural frontiers are usually far from population centers. Roads, or the thereof, can allow or make unprofitable both extraction and agricultural endeavors into the forest, as empirically assessed by Andersen (1996) and Pfaff et al. (2007), who observed that changes on road density in Amazon contributed to deforesting.

Government policies can influence forest retraction, such is the case of rural credit. The issue of unchecked credit and subsides will provide funding for property expansion, while better planned programs can create impediments for deforestation. (Fearnside, 2005) and Prates (2008) argue that monetary incentives such as price supports, credit concessions, and frequent amnesties for debt are government supported policies that cover cost of deforestation.

Geoclimatic variables also can influence deforestation, *e.g.*, high levels of precipitation increase risk of crop loss decreasing the profitability of plantations. In the other hand dry seasons ease the deforestation effort as illegal actions can be disguised as natural occurring fires. As discussed by Pivello (2011), Cerrado is a fire prone biome that can withstand natural fires that arise in the dry season, however Pivello states that the majority of wildfires in the cerrado region are caused by human endeavor, as a method to clear native vegetation and establish new pastures or crops. It is also noted by Pivello, that due to the easier conditions human induced fires are more present in the dryer-season, statement supported by data indicating that dryer-years have significant more wild fires, both in Amazon and in Cerrado.

Additionally, as already presented in the introduction, there is a understanding that a deforestation in developing countries is propelled by internal demand for agricultural, mineral, and forestry inputs (Allen and Barnes, 1985; Ehrhardt-Martinez, 1998; Barbier, 2004). In what concerns this, it is often theorised that after a certain level of income is reached the effect is inverted –deforestation diminishes with additional growth. This hypothesis, refereed as environmental Kuznets curve for deforestation (EKCd), is widely tested at country level (Caravaggio, 2020) with conflicting results. While estimating panel data on deforestation rates against a quadratic function of GDP studies such as Andrée et al. (2019), Chiu (2012), and Motel et al. (2009) find evidence for the existence of the EKCd, others (Barbier, 2004; Van and Azomahou, 2007; Leblois et al., 2017) indicate the contrary. There are also a number of studies that present mixed evidence based on data clustering, as Culas (2012) for continents or Damette and Delacote (2011) for richer and poorer countries. For a in depth review of EKCd studies at country level the reader might want to see Caravaggio (2020).

In county level studies Tritsch and Arvor (2016) and have found evidence in favor of EKCd in the Amazon; de Barros and Stege (2019) find similar results observing the Matopiba region –the northernmost part of Cerrado. Finally, Santiago and do Couto (2020) also confirmed the EKCd using municipal data on the Amazon, Matopiba and the states of *Paraná*, *São Paulo* and *Mato Grosso*. Despite results confirming EKCd, the majority of studies did not present tests concerning a possible cubic form for the EKCd hypothesis. Allowing for the possibility that after the first turning-point in deforestation, there is a second turning-point where deforestation rises again and the curve will form a upside-down "U" followed by a normal "U" as noted by Caravaggio (2020). As shown in Steinkraus (2017) –which observed the EKC in green house gas emissions– by adding a cubic income term on to the regression and verifying its significance one can test for this hypothesis.

3 Data

Our aim is to inquire which variables influence Cerrado's deforestation at a county level, as it is usually the most disaggregated level of Brazilian datasets. Native vegetation suppression data concerning Cerrado is provided by Brazil's National Institute of Space Research (INPE) as *shapefiles*.This data-set was published biennially from 2002 to 2012, and yearly from 2013 onwards. Given this, we choose to aggregate its yearly portion of our data into biennial values by merging then together. Adding to this, the data does not follow the Gregorian year, instead, measures are made at August 1st every two years. Those two time-spam problems call for adjustments to our explanatory variables, i.e., any yearly data must be converted to what we call the INPE's year[2].

Price information on commodities in Brazil are available at different sources. The Municipal Agricultural Production database (PAM) managed by Brazilian Statistical Institute (IBGE) provides data on quantity of soybeans produced and total revenue from soy beans, at farms gate, for each municipality within our time-span in a yearly periodicity, therefore, necessary adjustments were made. From that obtaining prices for farm gate soy is trivial. Additionally, we also collected price information on charcoal originated from non-renewable plant extraction, which is provided by IBGE on its municipal Production of Plant Extraction and Forestry (PEVS) dataset, where the same treatment as soybeans is used.

For beef prices, an equivalent database from the same source –Municipal Livestock Production (PPM)– does not inform revenue values for bovine meat production. Therefore, we calculate farm gate prices in a similar manner proposed in Arima et al. (2007)[3]. Using county export quantities and values of beef products, provided by the Brazilian Trade Ministry (COMEXDATA), we obtained –after performing a currency conversion– export prices of meat. However, those prices are only available in a fraction of all Brazilian municipalities, which we refer as Meat Market-Hubs (MMH). In order to estimate farm gate prices, the distances from each county[4] to the nearest MMH is calculated via GIS using euclidean distances from each county centroid and multiplied by a transport cost estimate suggested in Arima et al. (2007)[5] resulting in a transportation cost of each count to nearest MMH, which in turn is subtracted from the export prices to obtain farm gate prices for each county on each year. Values are measured in BRL per *arroba* of cattle meat, which is equivalent to 15kg.

Rural credit, concerning both that destined for agriculture and livestock, was obtained from the Brazilian Central Bank, for each municipality by year. To assess credit density by municipality the total value of rural

[2]By aggregating them proportionally after values are deflated, *e.g.*, in order to construct the 2004 data point for soybean prices we use 5/12 of deflated value and quantity for the year 2002, the complete value and quantity of 2003, and 7/12 of the year 2004, only then prices are calculated. For those variables were means are used the proportions are 5/24, 1/2 and 7/24 respectively.

[3]In Arima et al. (2007), slaughterhouse prices were obtained thought field interviews, Hargrave and Kis-Katos (2013) used an analogous technique together with a closed access database slaughterhouse prices to estimate the same variable.

[4]Prices are only calculated for municipalities that, according to PPM, had at least one cattle head within a INPE's year, for those without cattle the price is set to zero.

[5]The transport cost on unpaved road was used, which in 2000 was 0.31 R$ ton^{-1} km^{-1}.

credit is divided by the initial non-forested Cerrado area for each municipality, as in accordance to Hargrave and Kis-Katos (2013). To allocate for the possibility of a non linear effect of this variable the squared value is also computed.

Information on environmental policing is provided by IBAMA, since specific date is informed, no transformations were necessary. Fine intensity is computed identically to Hargrave and Kis-Katos (2013), where data of issued fines per county per period is divided by municipal deforestation on the same period. These three variables are converted to natural logarithms and to allow for zeros –in both monetary values and quantities– all entries have one added to it.

Precipitation levels are borrowed from Camarillo-Naranjo et al. (2019), where they are presented in a monthly basis from 1900 to 2019, we choose to create a variable counting the number of months –up to 24 in a given two-year period– were there was a historical deviation of at least two standard deviation more –for wet months– or less –for dry months– from the historical mean of each month for each municipality, *i.e.*, two variables are created: number of relative dry months in the period; and number of relative wet months in the period. For clarification equation (1) presented bellow describes how variable was created, where P_{imt} is the precipitation level of municipality i in month m in the year t, Z is a standardized variable, D and W are dummies for extreme dry or wet months.

$$
\begin{aligned}
&Z_{P_{imt}} = \frac{P_{imt} - \overline{P_{im}}}{s_{P_{im}}} \\
&D_{imt} = \begin{cases} 1, \text{if } Z_p < -2. \\ 0, \text{otherwise.} \end{cases} \quad \text{similarly,} \quad W_{imt} = \begin{cases} 1, \text{if } Z_p > 2. \\ 0, \text{otherwise.} \end{cases} \\
&DryMonths_{it} = \sum_m D_{imt}, \qquad WetMonths_{it} = \sum_m W_{imt}
\end{aligned} \tag{1}
$$

Municipal GDP per capita is obtained from IBGE and is transformed into the INPE's year, in order to test for the presence of a EKCd we create quadratic and cubic versions of the variable. All monetary values –prior to calculating prices if possible– are deflated to 2000 BRL levels using IPCA indexer, monthly data is deflated accordingly to January 2000 levels.

3.1 Sample Selection

Given characteristics of the database, some adjustments in the sample had to be performed. First the sample contains only municipalities with at least 75% of its area within Cerrado's frontier. Also, the sample is reduced to municipalities which in July 2000 had at least 10% of its area covered with primary Cerrado forest. Those selection processes reduce our sample from 1388 to 942 municipalities.[6]. Descriptive statistics of this sample are presented on table 1. Additionally, municipalities that did not produce soy in all studied periods were also removed. This reduces our sample further to 392 municipalities. This reduction allows a better evaluation of the influences of deforestation in soy producing regions. Finally, 4 municipalities that were created after year 2000 had to be dropped to balance the panel.

[6]These cutoff points are arbitrary and a sensitivity analysis with alternative cutoff points will be performed in future versions of this manuscript

Table 1: Descriptive Statistics of Restricted Sample(>75% Cerrado and >10% Forest)

Variable	Scale	Mean	SD.	Min.	Max.
ln Deforestation	ln (ha + 1)	6.489	2.169	0.000	11.75
Meat Price	BRL per 15kg	58.22	26.55	10.48	394
Soy Price	BRL per 60kg	12.78	10.93	0	171
Charcoal Price	BRL per kg	0.165	0.464	0	14
ln Fine Intensity	$\ln \frac{(\text{Fines in BRL} + 1)}{(\text{Defor. in ha} + 1)}$	0.144	4.721	−10.53	16.44
ln State Fine Intensity	$\ln \frac{(\text{State Fines in BRL} + 1)}{(\text{State Defor. in ha} + 1)}$	4.673	1.409	0.000	9.428
ln Credit Density	$\ln \frac{(\text{Cred. in BRL} + 1)}{(\text{Ini. Land in ha} + 1)}$	5.893	1.562	−10.868	10.359
Wet Months in Period	Num.of Months	1.037	1.092	0	6
Dry Months in Period	Num.of Months	0.144	0.488	0	8
ln GDP per capita	ln GDP/pc	8.522	0.752	6.485	11.637

Statistics refer to N = 8,541 observations for 949 municipalities spamming 18 years in a two by two basis. All prices and economic values are expressed in constant 2000 Brazil Reais (BRL).

4 Empirical Strategy

On recent economic studies of deforestation, panel analysis was been the main method for econometric inference, both on country level studies and those observing municipalities. For the latter, spatial correlation was identified by a number of studies as of importance (Pfaff et al., 2007; Hargrave and Kis-Katos, 2013), which are dealt with spatial econometrics.

Our strategy comprises in, first, finding the best functional form using traditional panel modeling, also identifying whether fixed or random effects are more appropriate. Subsequently we use the selected function, instruments and controls in the spatial panel estimation. Within the function form election we test for nonlinear effects of the GDP and rural credit variables by adding squared and cubed forms of each, and picking the functional form with best fit[7].

4.1 Formal and Empirical Models

Based on what was previously discussed the desired model to be estimated is represented by equation (2), where following the assumptions of the crime rational choice deforestation levels will be function of predicted revenue, costs and punishment, with the added control of the EKCd hypothesis. In our empirical model, equation (3), revenue is represented by prices of agricultural and executive output (soy, meat, charcoal); costs are partly omitted except for credit availability –which decreases costs for deforestation and cultivation– and climate variables; for

[7] Estimates without the final set of nonlinear variables, or with specific combination, are available by request.

the punishment variable only certainty of punishment is accounted for by the intensity of environmental fines.

$$DEF = f(Revenue,\ Cost,\ Punishment(\ certainty,\ severity,\ celerity),\ GDP) \tag{2}$$

$$\begin{aligned}\ln DEF_{it} &= \alpha_i + \alpha_t + \beta_p PRICES_{it} + \beta_F FineInt_{it} + \beta_c CreditDens_{it} + \beta_{c2} CreditDens_{it}^2 \\ &+ \beta_w WetMonths_{it} + \beta_d DryMonths_{it} + \beta_{g1} \ln(GDPpc_{it}) + \beta_{g2} \ln(GDPpc_{it})^2 + \beta_{g3} \ln(GDPpc_{it})^3 + \varepsilon_{it}\end{aligned} \tag{3}$$

were, $PRICES_{it}$ is a matrix composed of output prices (soy, meat, charcoal) for each county for each period; $FineInt_{it}$ represents the intensity of environmental fines in each county for each period; $CreditDens_{it}$ is the density of rural credit in each municipality for each period; $WetMonths_{it}$ and $DryMonths_{it}$ inform the number of abnormally wet and dry months for each county in each period; $GDPpc_{it}$ is municipal per capita GDP; α_i and α_t are county and period fixed effects; ε_{it} is assumed to be an i.i.d. error term; β_x are the linear coefficients of each variable.

4.2 Endogeneity and Instruments

It is easy to argue that environmental crimes and environmental law enforcement numbers to be simultaneously determined, as IBAMA concentrates its activity in counties with already high levels of deforestation, this means that environmental crimes and issued fines on environmental crimes are a function of each other, as criminals observe their punishment chance based on the number of fines, and fining activity occur where crimes are most committed. This creates an endogeneity problem within our analysis as the regression error term may be correlated with the predictor, the number of fines.

To solve for this problem we decided to employ an instrumental variables approach (IV) together with two-stage regression (2SLS). This method consist in estimating the problematic predictor using an instrument correlated with the predictor but not with the original dependent variable, as is shown in equation (4). The second stage is the estimation of our objective equation using the fitted values of the fist equation, as presented in equation (5). For such, we used state fine intensity as an instrument, mirroring what is proposed in Hargrave and Kis-Katos (2013), this consists in the number of fines within the state of the municipality, of all other counties in the Cerrado with the municipality removed.

$$x_{it} = \alpha_i + \alpha_t + \zeta z_{it} + \theta X_{it} + mu_{it} \tag{4}$$

$$y_{it} = \alpha_i + \alpha_t + \gamma \hat{x}_{it} + \beta X_{it} + \varepsilon_{it} \tag{5}$$

where x_{it} is the endogenous variable; α_i & α_t are fixed effects for individuals and time; z_{it} is the chosen instrument; $X_i t$ are the remaining variables; and both ε_{it} & μ_{it} are i.i.d. errors; ζ, θ, γ and β are linear coefficients to be estimated.

4.3 Spatial Panel Regression

Factors that influence deforestation can be –and usually are– spatial (Robalino and Pfaff, 2012). Therefore, a spatial model addressing possible spatial correlation such as a spatial autoregressive (SAR) and spatial error (SEM) models are advisable. The SAR model assumes that there is spatial auto-correlation of the dependent variable, while the SEM model assumes that there is a spatial relationship in the residuals, probably because omitted variables are of spatial nature. The panel version of such models are specified in Elhorst (2003, 2008) and a generalization of the composite model (SARAR) is provide by Millo and Piras (2012). We them will re-estimate the model of equation (3) including both spatial error correction (SEM) and spatial lag element (SAR) which follows the form:

$$\ln DEF_{it} = \lambda W \ln DEF_{it} + X_{it}'\beta + \alpha_i + \alpha_t + u_{it} \tag{6}$$

where W is the symmetric spatial k-nearest neighbours (KNN) matrix of degree 5, λ is the spatial spillover parameter from the SAR specification. The disturbance vector is the sum of two terms:

$$u_{it} = \rho W u_t + \varepsilon_{it} \tag{7}$$

with ρ as the spatial error parameter from the SEM specification. In order to control for endogeneity we will employ the Generalized Method of Moments (GMM) estimator for spatial models (Kapoor et al., 2007; Baltagi and Liu, 2011) which allows for two stage estimation using instrumental variables of SAR, SEM, and SARAR.

The usual interpretation of the parameter estimates as marginal effects is only possible for spatial error models, for the other two specifications the calculation of direct, indirect, and total impact is necessary. This happens because any increase in a variable x_{jt} for a municipality j will have a β impact on DEF_j, but given the spillover effect neighbour counties will suffer an impact equal to $\beta \cdot \lambda$. This spillover will also affect neighbors-of-neighbors by $\beta \cdot \lambda^2$ and so on, even coming back to the original municipality. To obtain the complete impact of each variable we perform an estimation according to the routine proposed in Piras (2014) using the statistical program R (R Core Team, 2020). To our understanding studies using spatial panel data before 2014 rarely present these impacts, and even more recent works may lack these results as a simple function is not present in the main package for spatial panel statistics in R, ”splm” (Millo and Piras, 2012).

5 Tests and Results

5.1 Panel Model

For better selecting our model specification we run some tests assessing which regression technique is more adequate to our data set, which can be seen on table 2. We begin comparing a pooled model with an location fixed effect model using a simple Chow test to verify whether the intercepts are identical across municipalities, which confirms the usage an fixed effects specification (FE). The next test employed is a Hausman test , which verifies if FE model and a random effects model (RE) are both consistence in the null hypothesis, or just FE is consistent. If both models are similar RE should be chosen given that it is more efficient. The results indicate FE as the better model.

Breusch-Pagan and Breusch-Godfrey tests verify for heteroscedastic and serially correlated errors respectively, results indicate that both problems are present. Therefore heteroscedasticity- and autocorrelation-consistent (HAC) standard errors need to be estimated, for such propose we chose to use Arellano et al. (1987) sandwich estimators for the robust covariance matrix. Last two tests are concerned with instrument strength and the consistency of 2SLS estimator compared to OLS, their results attest to the validity using 2SLS estimator for panel with the selected instrument.

Table 2: Tests for Panel Models

Test	Comparison	Statistic	Verdict
Chow Test	Pooled vs. Fixed Effects	F = 30.71 p-value < 0.001	Fixed Effects
Hausman Test	Fixed Effects vs. Random Effects	χ^2 = 74.623 p-value < 0.001	Fixed Effects
Breusch-Pagan	Homocedastic vs. Heteroscedastic	BP = 3576.2 p-value < 0.001	Heteroskedastic Errors
Breusch-Godfrey	Serial Correlation in idiosyncratic errors	χ^2 = 818.11 p-value < 0.001	Serial Correlation
Instrument Relevance	Relevant vs. Weak Instrument	F = 198.15 p-value < 0.001	Relevant Instrument
Wu-Hausman Test	2SLS vs. OLS	χ^2 = 30.356 p-value < 0.0474	2SLS

In table 3 the results for eight models are presented. With (1) thought (4) concerning the full sample with 942 municipalities observed for nine periods of two years. The other four models, from (5) thought (8), are of a restricted sample of 392 counties where soy was produced in every period of study. Models (1) and (5) are polled least squares; models (2) and (6) are demeaned individuals fixed effects; time dummies are added in models (3) and (7); and (4) and (8) are the second stage of a two staged regression with instrumentalized fines.

In what concerns prices, we can observe that they have no, or little, statistical significance in the more complete models (3 and 4). This may happen given some data collections problems such as, the data being biennial thus extremely aggregated, low individual variance of the prices, and high number of zeros given that counties that do not produce a good have zero prices.

Evidence for the second diagnostic is present if we observe models (2), (3) and (4), as in the same manner that individual fixed effects will nullify the effects of time invariant predictor –or even those with little variation, time fixed effects will hinder the response of variables with little between group variation. Together, in the two-way fixed effects form, variables who show little time and group variation may become non-significant in the model, in our opinion that is what is happening with prices in the model, *i.e.*, between group variation is already minimum for the exogenous defined prices, and within variation becomes insignificant when data is aggregated biennially.

For further investigation in the significance of the commodity pricing effects on deforestation we limited our sample to only those municipalities within our main sample that are soy producers. This strengthened our hypothesis, suggesting that two-way fixed effects and the biennial aggregation do not allow for a strong analysis of price-effects on deforestation. From the regression results we restrain ourselves in only stating that there is suggestive evidence, manly for cattle based products, of commodity pricing encouraging deforestation.

As for credit density, we can observe that the models with only individual fixed effects –(2) and (6)– indicate a negative inclined curve which would imply that rural credit curbs deforestation. However, given the trend nature of both rural credit (increasing with time) and deforestation (decreasing with time) an analysis without

Table 3: Panel Regression Results for Cerrado Deforestation

	ln *Deforestation*							
	Full sample				*Rsetricted sample: soy producers*			
	(1) Polled	(2) FE	(3) FE/TE	(4) IV FE/TE	(5) Polled	(6) FE	(7) FE/TE	(8) IV FE/TE
Meat prices	−0.001	0.0003	0.001*	0.0002	−0.002	0.005***	0.003***	0.003***
	(0.001)	(0.0005)	(0.0004)	(0.0005)	(0.002)	(0.001)	(0.001)	(0.001)
Soy prices	0.036***	0.007***	0.002	0.002	−0.016	0.023***	0.004	−0.001
	(0.005)	(0.002)	(0.002)	(0.002)	(0.013)	(0.007)	(0.003)	(0.004)
Charcoal prices	0.521***	0.021	−0.001	−0.003	0.730*	−0.031*	−0.021	−0.068***
	(0.163)	(0.020)	(0.013)	(0.020)	(0.405)	(0.018)	(0.019)	(0.025)
ln Credit Density	0.046	−0.166***	0.059	0.067*	−0.252***	−0.325***	0.044	0.102**
	(0.036)	(0.023)	(0.038)	(0.037)	(0.087)	(0.036)	(0.036)	(0.042)
ln Credit Density^2	−0.022***	−0.023***	0.012***	0.011***	−0.009	−0.029***	0.015***	0.010**
	(0.004)	(0.002)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.004)
ln Fine Intensity	0.009	−0.036***	−0.038***	−0.132***	0.018	−0.043***	−0.041***	−0.191***
	(0.008)	(0.004)	(0.003)	(0.020)	(0.014)	(0.006)	(0.005)	(0.029)
ln GDPpc	25.137**	37.866***	35.167***	40.572***	−26.998	88.712***	51.157***	61.016***
	(11.226)	(6.110)	(4.413)	(5.207)	(22.766)	(15.100)	(8.685)	(11.043)
ln GDPpc^2	−3.281**	−4.242***	−3.655***	−4.279***	2.392	−9.594***	−5.376***	−6.553***
	(1.301)	(0.711)	(0.508)	(0.598)	(2.534)	(1.706)	(0.961)	(1.218)
ln GDPpc^3	0.137***	0.154***	0.126***	0.150***	−0.067	0.343***	0.189***	0.235***
	(0.050)	(0.027)	(0.019)	(0.023)	(0.093)	(0.064)	(0.035)	(0.045)
Dry Months	−0.006	0.033	0.158***	0.175***	−0.069	−0.018	0.075***	0.076**
	(0.059)	(0.023)	(0.022)	(0.025)	(0.076)	(0.032)	(0.029)	(0.037)
Wet Months	−0.056**	−0.019*	−0.015	−0.003	−0.072**	−0.036**	−0.041**	−0.031*
	(0.022)	(0.011)	(0.011)	(0.011)	(0.035)	(0.017)	(0.017)	(0.019)
Individual FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	No	No	Yes	Yes
Instruments	No	No	No	Yes	No	No	No	Yes
Observations	8,541	8,541	8,541	8,541	3,528	3,528	3,528	3,528
R^2	0.118	0.269	0.467	—	0.113	0.363	0.552	—
Adjusted R^2	0.117	0.176	0.399		0.110	0.281	0.493	
F Statistic	103.7***	253.0***	349.6***	5,488.3***	40.5***	162.1***	201.8***	2,610.9***

Notes: Significance levels * $p<0.1$; ** $p<0.05$; *** $p<0.01$. R^2 and Adjusted R^2 reported are for fixed effect models with demeaned values of individual and dummies for time. Models have Arellano et al. (1987) robust standard errors.

the time dummies will be misleading. According to models (4) and (8) we have an positive inclined curve (with positive derivative) revealing a boost effect, what is corroboreeing Fearnside (2005). This impact is grater when the sample is centered around soy producers, a sign that those use the credit for illegal land reclamation more often.

Fine intensity shows significant hindering impact on deforestation in both samples which agrees with what is reported in Hargrave and Kis-Katos (2013). The 2SLS model shows to have a better performance than traditional OLS and present an greater effect of fines on the struggle against deforestation. The difference between main sample and soy producers sample shows that environmental policing is more efficient in the latter as well.

The results for GDP per capita impacts confirm an EKCd in Cerrado with a caveat, there is a right tail where deforestation increases again. For the main sample model (4), the tipping point is around BRL_{2000} 860 per capita and deforestation rises again at BRL_{2000} 7,881,273 as our data is limited by BRL_{2000} 655 and 113,191 the EKCd hypothesis is indeed confirmed. For soy producers there is no tipping point –only an inflection at BRL_{2000} 10,883– as the curve is always increasing, suggesting that aggregate demand forces exert significant pressures on soy plantations expansion.

For better clarification on why the EKCd is not valid here, the separation of rural and non-rural GDP may be necessary, as soy producers counties may have a significant proportion of its output only on soybean production. If so, there is evidence of the predatory nature of soy cultivation, where farm expansion is always pursued, but profits are not dispersed within the municipality. This is contrary to what EKCd states where wealthier populations pursue the end of deforestation, *i.e.*, the municipalities are rich but the population is not, therefore there are no incentives for decreasing deforestation.

For our final set of variables we have the climate indicators. In our main sample we can see that dry months can have a significant impact on deforestation, endorsing the hypothesis of landowners taking advantage of the dryer than expected months to clean land proposed by Pivello (2011). There is a smaller impact of dry months when observing soy producers, probably because dryer than expected months may induce crop loss. The same is applied to wetter than expected months, as a farmer will be occupied in replanting lost crops he is less able to expand its property, which is also found in Hargrave and Kis-Katos (2013). However, for the general sample where cattle ranchers are better represented wet months have no impact, while land expansion on dryer months is boosted. For a better understanding of specific mechanisms a more specific analysis regarding forest fires –data available by INPE in DETER platform– and deforestation seasons is advisable.

5.2 *Spatial Model*

Table 4 presents the preliminary regression results for six spatial panel models. Similarly to table 3 they are divided into full sample (9)–(11) and soy producers (12)–(14). Models (9) and (12) are of SAR specification, (10) and (13) are SEM, and (11) and (14) are mixed models. All models are of within fixed effects, have time dummies and instrumentalized fine intensity.

The spatial lag coefficient of deforestation λ has high and significant values, around 0.9, in all models estimated. This corroborates with other studies which indicate that deforestation has a spillover effect among municipalities (Robalino and Pfaff, 2012; Hargrave and Kis-Katos, 2013). In this case the effect is that a one percent rise in deforestation in a given municipality will result in a 0.9% rise in deforestation on neighbor municipalities.

The spatial error component ρ provides more efficient results for our models, as it removes from the error component the spatially correlated residuals that arise from omitted relevant variables with an spatial distribution. Comparing the SAR specifications with the mixed specifications we can see that the efficiency gain with the spatial error component is important, as some parameters become significant in the presence of it. The only exception to this is the the parameter for fine intensity, we believe that this is due the chosen instrument being to similar in neighboring counties, therefore its effect is captured by the spatial lag coefficient.

Table 4: Spatial GMM Regression Results for Cerrado Deforestation

	ln *Deforestation*					
	Full sample			*Restricted sample: soy producers*		
	(9) SAR	(10) SEM	(11) SARAR	(12) SAR	(13) SEM	(14) SARAR
Spatial lag (λ)	0.9127***	—	0.9063***	0.8851***	—	0.8954***
	(0.0366)		(0.0241)	(0.0488)		(0.0304)
Meat prices	0.0001	0.0001	0.00008	0.0005	0.001	0.0006*
	(0.0003)	(0.0006)	(0.0001)	(0.0006)	(0.001)	(0.0003)
Soy prices	0.0011	0.0022	0.0006	0.0012	0.0011	−0.0003
	(0.0012)	(0.0015)	(0.0009)	(0.0034)	(0.0048)	(0.0025)
Charcoal prices	0.0081	0.0009	0.0058	0.0189	−0.0513	0.0050
	(0.0175)	(0.0212)	(0.0138)	(0.0279)	(0.0393)	(0.0223)
ln Credit Density	−0.0037	0.0199	0.0099	0.0059	0.1000***	−0.0014
	(0.0112)	(0.0133)	(0.0090)	(0.0252)	(0.0376)	(0.0198)
ln Credit Density^2	0.0044***	0.0047***	0.0043***	0.0045	0.0024	0.0041**
	(0.0012)	(0.0015)	(0.0009)	(0.0024)	(0.0036)	(0.0018)
ln Fine Intensity	−0.0024	−0.1493***	−0.0071	−0.0135	−0.2013***	−0.0152*
	(0.0120)	(0.0313)	(0.0060)	(0.0143)	(0.0404)	(0.0080)
ln GDPpc	3.1237	17.107***	4.8061**	12.643**	30.444***	10.421**
	(3.1486)	(3.9864)	(2.2052)	(6.4138)	(8.8963)	(4.9586)
ln GDPpc^2	−0.2905	−1.7711***	-0.4941**	−1.3683**	−3.3318***	−1.1108**
	(0.3581)	(0.4531)	(0.2515)	(0.7095)	(0.9838)	(0.5499)
ln GDPpc^3	0.0087	0.0608***	0.0169*	0.0494**	0.1218***	0.0396*
	(0.0135)	(0.0170)	(0.0095)	(0.0261)	(0.0362)	(0.0202)
Dry Months	0.0225	0.0761**	0.0259**	0.0065	−0.0157	0.0154
	(0.0196)	(0.0318)	(0.0116)	(0.0249)	(0.0438)	(0.0151)
Wet Months	0.0047	0.0097	0.0009	−0.0051	−0.0365	−0.0028
	(0.0077)	(0.0153)	(0.0039)	(0.0116)	(0.0232)	(0.0062)
Spatial error (ρ)	—	0.5586	−0.8890	—	0.4866	−0.8769
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,541	8,541	8,541	3,528	3,528	3,528

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01.

As discussed in the section 4, the calculation of direct, indirect and total impacts is necessary to visualize marginal effects of both SAR and SARAR models. Table 5 presents the effects for the SARAR models, as their are of greater interest. In order to have an clearer analysis, only significant variables –of p-value < 0.10– have their impacts shown.[8]. The direct effects columns shows what is the marginal impact in a given municipality of a

[8]Other impacts are available on request.

one unit rise of a variable in that same municipality after the feedback loop is calculated. Indirect effect portrays the marginal change of deforestation on a given county when all other counties have a rise in the studied variable. Finally, total effect is a junction of both, representing the marginal effect on deforestation of all municipalities changing a given variable by one. It is interesting to note that the total effects displayed in table 5 are similar to the results of the non spatial models in table 4, it is then useful to think table table 5 as a decomposition of local vs. global effects of the results presented by the panel models.

Table 5: Marginal Impacts of Variables for SARAR Models

	ln *Deforestation*					
	Full sample			*Restricted sample: soy producers*		
	Direct	Indirect	Total	Direct	Indirect	Total
Meat Prices	—	—	—	0.0009	0.0051	0.0060
ln Credit Density^2	0.0063	0.0373	0.0436	0.0060	0.0324	0.0384
ln Fine Intensity	—	—	—	-0.0220	-0.1181	-0.1402
ln GDPpc	7.0258	41.602	48.6286	15.085	80.944	96.030
ln GDPpc^2	-0.7223	-4.2773	-4.9997	-1.6081	-8.6287	-10.236
ln GDPpc^3	0.0247	0.1463	0.1710	0.0574	0.3083	0.3657
Dry Months	0.0378	0.2242	0.2621	—	—	—

6 Conclusion

Based on panel data of 949 municipalities from 2002 to 2018, this study provided empirical evidence on the drivers of deforestation in the Cerrado biome of Brazil. It investigated how rural and environmental factors may affect the decision to deforest this biome. Among these we looked into the effects of policy and economic variables. We also observed the influence of extreme climate conditions on the deforestation process. Our analysis observed what drives deforestation at municipal level in two contexts, first for all the cerrado biome, and then in the municipalities that are soybeans producers.

Some hypothesis were tested along the study. By measuring the non linearly effects of GDP per capita we were able to assess the existence of Environmental Kuznets Curve for deforestation in the biome, but when observing only soy producers we found evidence against EKCd being present. Our results indicate that agricultural incentives, represented by rural credit availability is positively correlated with deforestation rather than defer it, this effect is even larger for soy producers, and agrees with previous literature that indicate rural credit as funding for deforestation. Similarly to what was shown for the Amazon, we found evidence that fine intensity, as a proxy for certainty of punishment, discourages deforestation on both samples. For our most innovative result we observed evidence that the dry climate of the Cerrado would be another transmission channel affecting the deforestation process manly for non-soy producers. We also verified the spatial nature of deforestation, confirming that a spillover effect is present in the region.

These findings can guide a number of policy improvements. First, deforestation is responsive to government incentives of rural credit and subsides, therefore policymakers should restrict the supply of such benefits in areas with high deforestation, or implement new incentives to the conservation of the biome. Results also show that environmental policing is effective against deforestation is this region, and that IBAMA operations should be encouraged rather than dismantled in the country. The evidence that larger dry season may incentives deforestation is alarming given the predictions of IPCC on climate change for the next years. This raises the need to intensify environmental surveillance and punishments during those periods, and the need of enhancing environmental command and control policies.

Acknowledgments We would like to thank Brazil's Coordination for the Improvement of Higher Education Personnel (CAPES) for funding related to this work.

References

Allen, J. C. and Barnes, D. F. (1985). The causes of deforestation in developing countries. *Annals of the association of American Geographers*, 75(2):163–184.

Andersen, L. E. (1996). The causes of deforestation in the brazilian amazon. *The Journal of Environment & Development*, 5(3):309–328.

Andrée, B. P. J., Chamorro, A., Spencer, P., Koomen, E., and Dogo, H. (2019). Revisiting the relation between economic growth and the environment; a global assessment of deforestation, pollution and carbon emission. *Renewable and Sustainable Energy Reviews*, 114:109221.

Angelsen, A. (1999). Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights. *Journal of development economics*, 58(1):185–218.

Arellano, M. et al. (1987). Computing robust standard errors for within-groups estimators. *Oxford bulletin of Economics and Statistics*, 49(4):431–434.

Arima, E. Y., Simmons, C. S., Walker, R. T., and Cochrane, M. A. (2007). Fire in the brazilian amazon: a spatially explicit model for policy impact analysis. *Journal of Regional Science*, 47(3):541–567.

Assunção, J., Gandour, C., and Rocha, R. (2015). Deforestation slowdown in the brazilian amazon: prices or policies? *Environment and Development Economics*, 20(6):697–722.

Baltagi, B. H. and Liu, L. (2011). Instrumental variable estimation of a spatial autoregressive panel model with random effects. *Economics Letters*, 111(2):135–137.

Barbier, E. B. (2004). Explaining agricultural land expansion and deforestation in developing countries. *American Journal of Agricultural Economics*, 86(5):1347–1353.

Becker, G. S. (1968). Crime and punishment: An economic approach. In *The economic dimensions of crime*, pages 13–68. Springer.

Binswanger, H. P. (1991). Brazilian policies that encourage deforestation in the amazon. *World Development*, 19(7):821–829.

Brannstrom, C., Jepson, W., Filippi, A. M., Redo, D., Xu, Z., and Ganesh, S. (2008). Land change in the brazilian savanna (cerrado), 1986–2002: Comparative analysis and implications for land-use policy. *Land use policy*, 25(4):579–595.

Camarillo-Naranjo, J. M., Álvarez-Francoso, J. I., Limones-Rodríguez, N., Pita-López, M. F., and Aguilar-Alba, M. (2019). The global climate monitor system: from climate data-handling to knowledge dissemination. *International Journal of Digital Earth*, 12(4):394–414.

Caravaggio, N. (2020). Economic growth and the forest development path: A theoretical re-assessment of the environmental kuznets curve for deforestation. *Forest Policy and Economics*, 118:102259.

Chiu, Y.-B. (2012). Deforestation and the environmental kuznets curve in developing countries: A panel smooth transition regression approach. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 60(2):177–194.

Cropper, M. and Griffiths, C. (1994). The interaction of population growth and environmental quality. *The American Economic Review*, 84(2):250–254.

Culas, R. J. (2012). Redd and forest transition: Tunneling through the environmental kuznets curve. *Ecological Economics*, 79:44–51.

Damette, O. and Delacote, P. (2011). Unsustainable timber harvesting, deforestation and the role of certification. *Ecological Economics*, 70(6):1211–1219.

de Araújo, T. L. K., Sousa, P., de Miranda Azeiteiro, U. M., and da Maia Soares, A. M. V. (2021). Brazilian amazônia, deforestation and environmental degradation: Analyzing the process using game, deterrence and rational choice theories. *Environmental Science & Policy*, 117:46–51.

de Barros, P. H. B. and Stege, A. L. (2019). Deforestation and human development in the brazilian agricultural frontier: an environmental kuznets curve for matopiba. *Revista Brasileira de Estudos Regionais e Urbanos*, 13(2):161–182.

De Souza, R. A., Miziara, F., and Junior, P. D. M. (2013). Spatial variation of deforestation rates in the brazilian amazon: A complex theater for agrarian technology, agrarian structure and governance by surveillance. *Land use policy*, 30(1):915–924.

Diniz, M. B., Oliveira Junior, J. N. d., Trompieri Neto, N., and Diniz, M. J. T. (2009). Causas do desmatamento da amazônia: uma aplicação do teste de causalidade de granger acerca das principais fontes de desmatamento nos municípios da amazônia legal brasileira. *Nova Economia*, 19(1):121–151.

Duboc, E., Costa, C. J., Veloso, R. F., Oliveira, L. d. S., and Paludo, A. (2007). Panorama atual da produção de carvão vegetal no brasil e no cerrado. *Embrapa Cerrados-Documentos (INFOTECA-E)*.

Ehrhardt-Martinez, K. (1998). Social determinants of deforestation in developing countries: A cross-national study. *Social Forces*, 77(2):567–586.

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International regional science review*, 26(3):244–268.

Elhorst, J. P. (2008). Serial and spatial error correlation. *Economics Letters*, 100(3):422–424.

Fearnside, P. M. (2005). Deforestation in brazilian amazonia: history, rates, and consequences. *Conservation biology*, 19(3):680–688.

Godoy, R. and Contreras, M. (2001). A comparative study of education and tropical deforestation among lowland bolivian amerindians: forest values, environmental externality, and school subsidies. *Economic Development and Cultural Change*, 49(3):555–574.

Godoy, R., Groff, S., and O'Neill, K. (1998). The role of education in neotropical deforestation: Household evidence from amerindians in honduras. *Human Ecology*, 26(4):649–675.

Hargrave, J. and Kis-Katos, K. (2013). Economic causes of deforestation in the brazilian amazon: a panel data analysis for the 2000s. *Environmental and Resource Economics*, 54(4):471–494.

Jepson, W. (2005). A disappearing biome? reconsidering land-cover change in the brazilian savanna. *Geographical Journal*, 171(2):99–111.

Kapoor, M., Kelejian, H. H., and Prucha, I. R. (2007). Panel data models with spatially correlated error components. *Journal of econometrics*, 140(1):97–130.

Leblois, A., Damette, O., and Wolfersberger, J. (2017). What has driven deforestation in developing countries since the 2000s? evidence from new remote-sensing data. *World Development*, 92:82–102.

Machado, R. B., Ramos Neto, M., Pereira, P., Caldas, E., Gonçalves, D., Santos, N., K., T., and Steininger, M. (2004). Estimativa de perda da área do cerrado brasileiro. Technical report, Conservação Internacional, Brasília, DF.

Mahar, D. J. (1989). *Government policies and deforestation in Brazil's Amazon region.* World Bank.

Millo, G. and Piras, G. (2012). splm: Spatial panel data models in r. *Journal of statistical software*, 47:1–38.

Motel, P. C., Pirard, R., and Combes, J.-L. (2009). A methodology to estimate impacts of domestic policies on deforestation: Compensated successful efforts for "avoided deforestation"(redd). *Ecological economics*, 68(3):680–691.

Pendleton, L. H. and Howe, E. L. (2002). Market integration, development, and smallholder forest clearance. *Land economics*, 78(1):1–19.

Pfaff, A., Robalino, J., Walker, R., Aldrich, S., Caldas, M., Reis, E., Perz, S., Bohrer, C., Arima, E., Laurance, W., et al. (2007). Road investments, spatial spillovers, and deforestation in the brazilian amazon. *Journal of regional Science*, 47(1):109–123.

Pfaff, A. S. (1999). What drives deforestation in the brazilian amazon?: Evidence from satellite and socioeconomic data. *Journal of environmental economics and management*, 37(1):26–43.

Pichón, F. J. (1997). Settler households and land-use patterns in the amazon frontier: farm-level evidence from ecuador. *World Development*, 25(1):67–91.

Piras, G. (2014). Impact estimates for static spatial panel data models in r. *Letters in Spatial and Resource Sciences*, 7(3):213–223.

Pivello, V. R. (2011). The use of fire in the cerrado and amazonian rainforests of brazil: past and present. *Fire ecology*, 7(1):24–39.

Prates, R. C. (2008). *O desmatamento desigual na Amazônia brasileira: sua evolução, suas causas e conseqüências sobre o bem-estar*. PhD thesis, Universidade de São Paulo.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rivero, S., Almeida, O., Ávila, S., and Oliveira, W. (2009). Pecuária e desmatamento: uma análise das principais causas diretas do desmatamento na amazônia. *Nova economia*, 19(1):41–66.

Robalino, J. A. and Pfaff, A. (2012). Contagious development: Neighbor interactions in deforestation. *Journal of Development Economics*, 97(2):427–436.

Rocha, G. F., Ferreira, L. G., Ferreira, N. C., and Ferreira, M. E. (2011). Detecção de desmatamentos no bioma cerrado entre 2002 e 2009: padrões, tendências e impactos. *Revista Brasileira de Cartografia*, 63(3).

Santiago, A. R. and do Couto, H. T. Z. (2020). Socioeconomic development versus deforestation: Considerations on the sustainability of economic and social growth in most brazilian municipalities. *Environmental Development*, 35:100520.

Shukla, J., Nobre, C., and Sellers, P. (1990). Amazon deforestation and climate change. *Science*, 247(4948):1322–1325.

Skole, D. and Tucker, C. (1993). Tropical deforestation and habitat fragmentation in the amazon: satellite data from 1978 to 1988. *Science*, 260(5116):1905–1910.

Steinkraus, A. (2017). Investigating the effect of carbon leakage on the environmental kuznets curve using luminosity data. *Environment and Development Economics*, 22(6):747–770.

Tritsch, I. and Arvor, D. (2016). Transition in environmental governance in the brazilian amazon: emergence of a new pattern of socio-economic development and deforestation. *Land Use Policy*, 59:446–455.

Van, P. N. and Azomahou, T. (2007). Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation. *Journal of Development Economics*, 84(1):291–309.

Wyman, M. S. and Stein, T. V. (2010). Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in belize. *Applied Geography*, 30(3):329–342.

Zwane, A. P. (2007). Does poverty constrain deforestation? econometric evidence from peru. *Journal of Development Economics*, 84(1):330–349.